Available online at www.sciencedirect.com

ScienceDirect

Procedia Computer Science 52 (2015) 1198 – 1205

Procedia Computer Science

The 2nd International Workshop on Wireless Networks and Energy Saving Techniques (WNTEST 2015)

WSN in Monitoring Oil Pipelines Using ACO and GA

Ola E. Elnaggar[a], Rabie A. Ramadan[b], Magda B. Fayek[a,b,*]

[a]Cairo University, ola_alnaggar@yahoo.com,Egypt
[b]Cairo University, rabieramadan@gmail.com,Egypt

Abstract

Wireless Sensor Networks (WSNs) are one of the most important technologies in the fields of wireless networking today. WSNs have a vast amount of applications including sensors embedded in the outer surface of pipeline or mounted along the supporting structure of bridges, robotics and health care. In this paper, we study the issues of linear sensor placement to monitor oil pipelines. We address the problem of optimal number of sensors to be deployed given initial energy of each sensor node and message buffering limitations. The objectives of the deployment process are: 1) maximizing the coverage of the pipe, 2) producing a connected network, and 3) prolonging the overall network lifetime. The paper utilizes two of the evolutionary algorithms to solve the deployment problem which are Genetic Algorithms (GA) and Ant Colony Optimization (ACO). Extensive set of experiments are performed for performance evaluation.

Peer-review under responsibility of the Conference Program Chairs
Keywords: WSN; ACO; GA; oil pipelines; linear sensor placement;

1. Introduction

In WSN, wireless sensor nodes are small size with limited power and communication rang depends on the transmission power8. It may be infeasible or expensive to change batteries in sensor nodes once a wireless sensor network is deployed. Thus, it is critical and challenging to deploy sensor nodes effectively to form long-lived sensor networks under energy constraints.

*Corresponding author.
E-mail address:magdafayek@gmail.com

Peer-review under responsibility of the Conference Program Chairs
doi:10.1016/j.procs.2015.05.158

Although there are many constraints on sensors including sensors' initial energy, sensors' size, and small communication and sensing ranges, they are used in many critical applications such as military and health care applications 89. One of the important applications of sensor networks is oil monitoring application. However, the problem of oil monitoring can be classified into three categories. The first category involves the linear oil pipeline monitoring where the oil pipes are considered as straight lines, see Fig. 1 and their services need to be monitored the second category includes the oil pipeline and oil tanks monitoring where tanks could be far from each other and there are some obstacles among them, see Fig 2. The third category which is the hardest problem the oil pipes is not straight as well as the environment could have obstacles and noisy, see Fig. 3. Our focus in this paper is on the first category of linear pipeline monitoring. However, other categories are planned to be our future work.

Fig.1. Linear pipeline14

Fig.2. Oil tanks and pipeline farm14

Fig. 3. nonlinear oil pipelines14

Monitoring oil pipelines was the interest of many other research such as the ones presented in[1,2,4,6,6,10]. In[6], the authors proposed a frame work for sensor deployment for pipeline monitoring purpose. The paper proposed an architectural model for sensor deployment and discusses its performance. In[1], the authors study the problem of placing the sink-node to maximize the lifetime of the sensor network in a two-tiered wireless network. Furthermore, the placement of additional relay nodes and their power provisioning are also considered in[2]. As an extension to the work done in[2], the authors in4studied different sensor network architectures for monitoring long distance pipeline infrastructures. They consider wired sensor networks, RF wireless sensor networks, integrated wired and wireless sensor networks. In[7], the authors propose a transmission range distribution optimization scheme to maximize the network lifetime given fixed node locations. In[10], the authors considered adjustable sensor communication ranges to maximize the network lifetime.

The most related work to the proposed algorithms in this paper is the one presented in[10]. Yifeng et. al. in[10], proposed a mixed integer linear program for the linear sensor deployment on an oil pipeline. The authors focused on the deployment of sensors on one segment between two adjacent heat segments in a range of few kilometres. Different sensor communication ranges are considered in a form of sensors' power. The authors formulate the problem using Mixed Integer Liner Program (MILP) for optimal deployment to a given n sensors. They also proposed a greedy heuristic algorithm for suboptimal solution in which nodes close to the sink node should forward the received messages using the minimum power level, so it saves its energy for more messages to forward. As can be noticed that the proposed algorithms care only about the sensors connectivity without taking into consideration the coverage of the pipeline. As the MIPL would not be practical for large scale networks, this paper proposes two different greedy algorithms based on Genetic Algorithms (GA) and Swarm Intelligence. These two algorithms are compared to the greedy algorithm proposed in[10] for performance measure. The two proposed algorithms satisfies both coverage and connectivity requirements of WSNs.

The remainder of the paper is organized as follows. Section 2 presents the problem definition. The solution approaches is shown in section 3. Section 4 describes the using of greedy algorithm, GA and ACO to solve the problem. Section 5 presents the simulation and the comparison for the algorithms. Conclude the paper and points out our future work shown in Section 6.

2. Problem definition

Given a linear segment of oil pipeline ends with two heat stations. The pipe runs for few kilometres to tens of kilometres. This pipe needs to be efficiently monitored; in other words, the whole length of the pipe needs to be covered and the sensed information needs to be transmitted to a certain node named sink or base station. The sink node is supposed to be at one of the heat stations as can be seen in Fig. 4.

Therefore, it is assumed that there is an oil pipeline with length L that needs to be monitored with number of sensor nodes N (N1, N2... N_n) and two heat stations are distributed at the ends of the pipe. A sink node S is supposed to be deployed at one of the pipe's ends close to one of the heat stations. Sensors as well as the sink node are assumed to have limited capabilities including the communication range, the sensing range, and the scares of energy source. For instance, Fig. 4 shows the deployment of five sensors on a pipe of length L. Sensor nodes forward the sensed data through multihop to the sink node S. That is, node N1 sends its data to node N2, and N2 sends its data as well as the relayed data to node N3 and so on without interweaving transmission among the nodes. The problem is as long as the sensor is close to the sink node, its energy gets depleted faster than other nodes. Nodes close to the sink take the responsibility of sending its data as well as forwarding all of the received messages from other nodes. Therefore, the deployed sensor networks lifetime depends on the energy of the nodes close to the sink. At the same time, the deployed nodes suffer from small buffer size where messages could be dropped due to non-availability of a space to be saved at.

This paper investigates an efficient deployment scheme that prolongs the overall sensor networks lifetime. At the same time, the proposed deployment scheme should satisfy two important requirements which are oil pipe coverage and network connectivity. In addition to these two requirements, the buffer limitations and the sensing rang are considered. Nodes' connectivity requires nodes to be close to each other which lead to more number of nodes to be used. This becomes a challenge when limited numbers of nodes are available. Taking into consideration sensors multiple power levels might help in increasing the nodes lifetime as well as reduces the number of used nodes.

In the following section, the proposed deployment approaches are explained. The paper starts formulating the problem in a Mixed Integer programming form (MILP). The greedy algorithm proposed in[10] for solving similar problem followed by our proposed approaches, deployment sensor nodes with communication rang only then deployment sensor nodes with communication, buffering and sensing rang using Genetic and ACO.

3. Solution approaches

In this section, we describe our approaches for solving the sensor deployment problem for linear oil pipelines. The section starts by stating the greedy algorithm proposed in[10] followed by our two approaches which are the Genetic Algorithms (GA) and Ant Colony .

3.1 Greedy algorithm

The authors in 10 solved the problem of linear sensor deployment using what is called Greedy algorithm. The greedy algorithm starts with assigning the highest power level (see Table 1) for all sensor nodes. While the coverage of the sensor nodes is larger than the length of pipeline L, we can decrease the power level of the critical sensor node that consumes the most energy until no further improvement to the lifetime can be obtained. That is, decreasing the power level for the critical sensor node will lead to a coverage being less than L, or all sensor nodes already operate at the lowest power level. This approach is denoted as the contraction (from high to low: H-to-L) heuristic scheme. The outline for the contraction heuristic scheme is shown in[10].

3.2 Deployment sensors with communication rang

In the first experiment, the proposed deployment scheme should satisfy two important requirements which are oil pipe coverage and network connectivity using GA and ACO and maximize WSN lifetime. Sensor nodes in this experiment with communication rang only.

3.2.1 Deployment using GA

This section elaborates on the first proposed algorithm which is the Genetic Algorithm (GA). GA is based on principle of survival of the fittest. It is progress through a simple cycle of processing stages: initial population, evaluation of fitness function, operator for selection, crossover, and mutation. The individual are encoded in the population strings known as chromosomes. After the encoding of chromosomes is occurred then the fitness of individual in a populations are calculated see Fig. 5. Then, two parents with high fitness are selected. Crossover and mutation done on the selected parents. GA stopped when the solution is found or the maximum number of iterations is reached[3,5].

For our problem, a chromosome is considered to be a solution or a deployment scheme for the pipe. A chromosome consists of the communication rang for each sensor. An efficient coding scheme for chromosomes makes it beneficial for calculation of fitness operator. This measure is used to select probabilistically individual for crossover. Crossover operator fuses the information continued within pairs of selected parents by placing random subsets of information from both parents. By the impact of random subsets children chromosomes may or may not have higher fitness value than their parents.

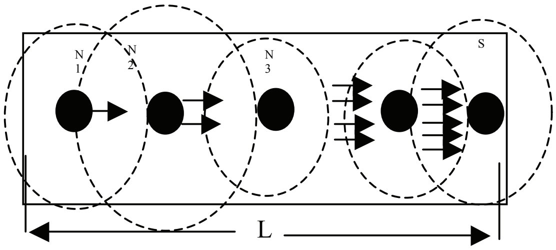

Fig.4. Oil pipeline

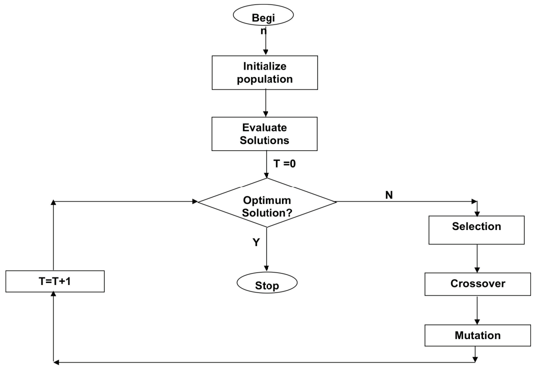

Fig.5. GAs mechanism

6	4	5	4	3	2	....	....	1	1

Fig.6. GA chromosomes with length n equal the number of sensors will deployment on pipe.

cross over point

parent1:

6	6	5	4	5	3	2	1	2	1

parent2:

5	4	2	2	6	4	3	1	1	2

child1:

5	4	2	2	5	3	2	1	2	1

child2:

6	6	5	4	6	4	3	1	1	2

Fig. 7: cross over in GA

As shown in Fig.6, the first step during GA is initial population creation, requirement for number of sensors, number of communication range and size of population. Initial populations consist of number of chromosomes used to create next generation. The number of the sensor nodes is the chromosome length. The communication level of the sensor is the gene (random number from 1 to 6). In the chromosome, the distance d1 between sensor number one and two is communication level 6 (from Table 1 R6 = 87.48). The distance between sensor 2 and 3 is communication level 4. The length covered by the chromosome is the sum of d_i (i=1 to n).

In selection and crossover we select two parents from the population with high fitness. Chromosome fitness increases if the sensors' deployment of this chromosome covered the pipe with low power consumption. In this problem, we use single point crossover see Fig. 7.

In mutation, we select random point and flip the value with random number of communication level from 1 to 6, for instance. GA will stop after certain number of iteration and return the best chromosome.

3.2.2 Deployment using ACO

Ant Colony Optimization (ACO) is a class of algorithms, whose first member, called ant System, was initially proposed by Colorni, Dorigo and Maniezzo[11,12,13]. The main underlying idea, loosely inspired by the behaviour of real ants, is that of a parallel search over several constructive computational threads based on local problem data and on a dynamic memory structure containing information on the quality of previously obtained result. The collective behaviour emerging from the interaction of the different search threads has proved effective in solving combinatorial optimization (CO) problems.

The base of ACO is to simulate the real behaviour of ants in nature. The functioning of an ant colony provides indirect communication with the help pheromones, which ants excrete. Pheromones are chemical substances which attract other ants searching for food. The attractiveness of a given path depends on the quantity of pheromones that the ant feels. Pheromones excretion is governed by some rules and has not always the same intensity. The quantity of pheromones depends on the attractiveness of the route. The use of more attractive route ensures that the ant exudes more pheromones on its way back and so that path is more also attractive for other ants. The important characteristic of pheromones is evaporation. This process depends on the time. When the way is no longer used, pheromones are more evaporated and the ants begin to use other paths. We can understand ACO from next steps:
First step: for first sensor, *m* artificial ant start with random number from 1 to maximum number of communication levels (in this paper there are 6 levels).
Second step: each ant builds a solution by adding one communication level after the other until it reaches to the last sensor. The selection of the next communication range depends on the probability. The probability p^{i}_{k} of transition of a virtual ant from the node i to the node k is given by formula (1).

$$p^{i}_{k=(\eta i}{}^{\alpha}+\tau_i{}^{\beta})/\Sigma_{=(\eta ni}{}^{\alpha}+\tau_{ni}{}^{\beta}) \quad (1)$$

Where τ_i - indicates the attractiveness of transition in the past, η_i - adds to transition attractiveness for ants, $_{ni}$- set of nodes connected to point i, without the last visited point before i, β, α- system dependent parameters .
Third step: pheromone update, virtual ant is using the same reverse path as the path to the food resource based on his internal memory, but in opposite order and without cycles, which are eliminated. After elimination of the cycles, the ant puts the pheromone on the edges of reverse path according to formula (2).

$$\tau_{ij}{}^{t+1=}\rho\tau_{ij}{}^{t}+\Delta\tau^{t} \quad (2)$$

Where $\tau_{ij}{}^{t}$ - value of pheromone in step *t*, $\Delta\tau$- value by ants saved pheromones in step *t*. Values $\Delta\tau$ can be constant or they can be changed depends of solution quality.
Fourth step: At last, the pheromones on the edges are evaporated. The evaporation helps to find the shortest path and provides that no other path will be assessed as the shortest.

$$\tau_{ij}{}^{t+1=}(1\text{-}\rho)\,\tau_{ij}{}^{t} \quad (3)$$

Where ρ is a user-defined parameter called *evaporation coefficient.*
In our problem, a group of artificial ants searches solutions by starting each ant with random communication level for first sensor and completing the path until last one finishes depending on certain probability. This operation is inspired from the theorem 1 given in[10]:

Theorem 1. To maximize the lifetime of the WSN, for the sensor nodes Ni and Nj, the power level assignment should satisfy xi ≥ xj for i < j.

The high communication range is given high probability when the sensor is far away from the sink node and low probability is given to the nearest sensor to the sink node. Example on such setup is given in Fig. 8.

sensor no. 1 sensor no. n

Ant1:	4	4	2	3	3	…..	…..	1	1
Ant2:	5	5	4	4	4	…..	…..	2	2
.									
.									
Antn:	5	5	4	4	4	…..	…..	1	1

Fig. 8: ant colony paths

When all ants reach to the end of the path, the pheromone gets updated depending on the path length and the consumed power. Therefore, the path covers the pipe with law power consumption has high pheromone value. ACO will stop after reaches the maximum number of iterations and returns the best path.

3.3 Deployment sensors with communication, buffering and sensing range

In the second experiment, the proposed deployment scheme should maximize network lifetime, buffering and sensing percentage with full oil pipeline coverage and network connectivity using GA and ACO.In this section, we work on the above problem (first experiment) after adding some constraint. Deployment wireless sensors on oil pipeline with length L and send the sensed information to the sink node. Each sensor node in this section had buffering range (The maximum number of messages send by the sensor), sensing range (Area monitored by the sensor) and the communication range levels as stated in Table 1. Our objective is deployment connected sensor nodes to maximize network life time with maximum buffering and sensing percentage.

3.3.1 Deployment using GA

In this section, GA chromosome consists of sensors number and the communication ranges for each sensor see Fig.9. Each sensor has its buffering and sensing range. Buffering range of sensor S_i means the maximum number of message can send by S_i. In linear WSN, the number of sensor nodes before sensor S_n is n sensors. The maximum message number will reach to S_n is n message. Therefore, sensor S_i must satisfy formula (4).

$$B_{si} \geq i \tag{4}$$

Where B_{si} buffering range for sensor number i.

parent1:

4	2	14	10	....	5	3	17	12	1
1	2	1	6		6	6	4	3	2

swap

Parent 2:

5	17	12	3		9	1	16	2	4
6	6	2	2		1	1	5	4	2

Child:

5	17	12	3	.....	4	10	2	14	1
6	4	3	6		1	6	2	1	2

Fig. 9: crossover steps in GA.

First row in the chromosome includes the sensors number and the second one consists of the communication range. After crossover we need the sensors number without redundancy. So, our crossover illustrated in Fig. 9.
First step: select random cross over point.
Second step: swap the cell from parent 1 with the cell from parent 1 which has the same sensor number in the cell in parent 2 against the first cell.
Third step: repeat second step until reach to the crossover point.

3.3.2 Deployment using ACO

ACO in this section goes on the steps of ACO in Section 5. The different in the probability of select next node depend on the buffering, sensing and communication range.

Table 1: Communication range and power for sensors

Levels	1	2	3	4	5	6
R_i(meters)	5.49	15.85	39.01	60.96	71.02	87.48
P_i(mW)	33.1	39.6	45.0	51.1	57.2	61.9

4. Simulation results

4.1 Sensors with communication range deployment results

Based on the power model as shown in Table 1, Fig. 10 shows the normalized lifetime of the WSN under the equal-power schemes for different number of sensor nodes. The normalized lifetime of the network is the lifetime of the network divided by network baseline. The lifetime for the WSN with n_{min} sensor nodes is used as the network baseline where n_{min} is the minimum numbers of sensor can deployment on the oil pipeline with full coverage see formula (5).

$$n_{min} = L/Rc_{max} \tag{5}$$

Where L is oil pipeline length, Rc_{max} is the maximum communication range from Table 1.

From the results shown in Fig. 10 (a) where L=5000 m (pipe length) starting from using 165 sensors, it is clear that ACO and GA improve the normalized lifetime of the network more than the greedy algorithm. In Fig. 10 (b) L=15000 m, ACO and GA progress is much more than on the greedy algorithm starting from the number of sensors is equal to 350. From these set of experiments, it has been noticed that it is hard with GA to reach to the solution when the number of the sensor nodes needs to be deployed on the oil pipe is closed to n_{min}.

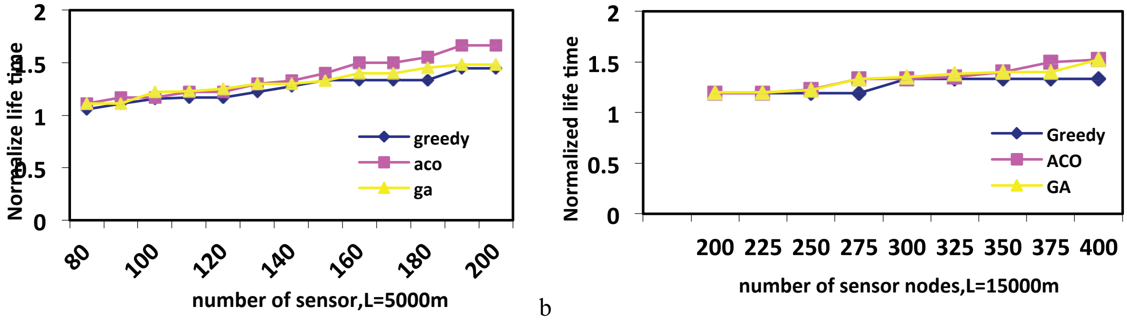

Fig. 10: Normalized life time for ACO, GA, and greedy algorithm (a) Pipe length=5000m; (b) Pipe length=15000m.

This problem didn't appear when using ACO deployment. In the next section will add some constraints to our problem. We set some more restrictions on the deployment where it will use sensors with buffering and sensing ranges are taking into consideration along with the communication ranges.

4.1 Sensors with communication, buffering and sensing range deployment results

In this section we illustrate the results when deployments of sensors with communication, buffering and sensing range limitations are used. The suggested length of the oil pipe is equal to 5000m as shown in Fig. 11.

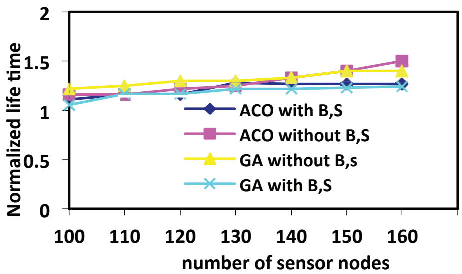

Fig.11: Normalized life time for ACO and GA after adding buffering and sensing range, L=5000m.

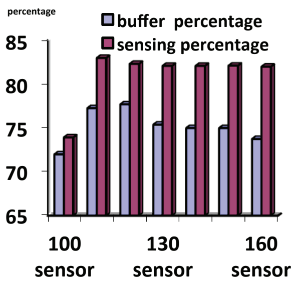

Fig. 12: Buffering and sensing percentage with different number of sensors using ACO deployment

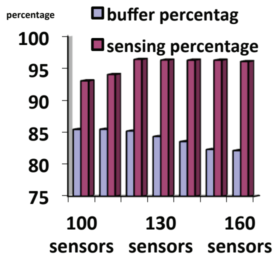

Fig. 13: Buffering and sensing percentage with different number of sensors using GA deployment.

From the results, start from point 140 (used 140 sensors), unfortunately, ACO and GA deployment sensors without buffering and sensing range improved network lifetime more than the experiment that use buffering and sensing range. At the same time, ACO lifetime is better than GA lifetime under same constrains (using buffering and sensing range).

Fig. 12, 13 illustrate the number of sensors affection on the buffering and sensing percentage.In ACO and GA, increasing the sensor nodes cause increasing in sensing percentage and decreasing in buffering percentage. When the number of sensor nodes increases the distance between the sensors decrease. The probability of satisfying the sensing concept increase. The opposite happened with buffering percentage; when the number of sensor nodes increase the required number of massages need to send increases. The maximum number of massages send by the sensors (buffering range) may be less than the incoming message. So, the probability of satisfy the buffering percentage decrease. In Figure 12, at point 115 (using 115 sensor nodes) sensing percentage start to increase whilst the buffering percentage start to decrease at point 120. The same happened with GA at point 120, we can see increase in sensing percentage and decrease for the buffering percentage.

5. Conclusion and Future Work

In this paper, we study the deployment of sensors in the linear WSN used to monitor oil pipeline. We first illustrate that the communication ranges and the power consumption for sensor nodes used in the problem. Based on sensors communication levels, we use ACO, GA, and greedy algorithm to see the best time. The best lifetime can be achieved when used ACO.

Then we add some constraint to the problem, adding Sensor nodes with communication, buffering and sensing range. The evaluation results show that, WSN lifetime using ACO and GA deployment with constraint close to WSN lifetime by using ACO and GA deployment without constraint until using 140 sensor nodes to deployment on pipe with L=5000m. After this point we can see the improvement of the lifetime of ACO and GA deployment without constraints. Buffering and sensing percentage in GA more than ACO.

For our future work, we plan to enhancement the deployment of sensor nodes to achieve the full sensing and buffering percentage with maximum lifetime.

Reference

1. J. Pan, Y. T. Hou, L. Cai, Y. Shi, S. X. Shen. Topology control for wireless video surveillance networks. In: *Proceedings of ACM Mobicom 2003*. ACM; 2003.
2. Y. T. Hou, Y. Shi, and H. D. Sherali. On energy provisioning and relaying node placement for wireless sensor networks. Technical report. Virginia Tech.; 2003.
3. M.Mitchell. Genetic Algorithms: An Overview; 1995. Complexity,pags 31-39.
4. A. C. Azubogu, V. E. Idigo, S. U. Nnebe, O. S. Oguejiofor. Wireless Sensor Networks for Long Distance Pipeline Monitoring. In World Academy of Science; 2013.
5. M. Dianati, I. Song,M Treiber. An Introduction of Genetic Algorithms and Evolution Strategies.
6. Ming Ma, Yuanyuan Yang. Sencar.An energy-efficient data gathering mechanism for large-scale multihop sensor networks. IEEE Transactions on Parallel and Distributed Systems; October 2007. 18(10):1476–1488.
7. M. Perillo, Z. Cheng, and W. Heinzelman. On the problem of unbalanced load distribution in wireless sensor networks. In *IEEE Globecom 2004*. Dallas. TX; Nov. 2004.
8. F. Shebli, I. Dayoub, J.M. Rouvaen,F. Shebli, I. Dayoub, J.M. Rouvaen, Th. Arampatzis, J. Lygeros, *Senior Member, IEEE*, S. Manesis, *Member, IEEE.* A Survey of Applications of wireless Sensors and Wireless Sensor Networks. 13th Mediterranean Conference on Control and Automation Limassol, Cyprus; 2005. Pages 719-724.
9. I.F. Akyildiz, W. Su, Y. Sankarasubramaniam, E. Cayirci. Wireless sensor networks: a survey. Computer Networks 38; 2002. pages 393–422.
10. Y. Guo, F. Kong, D. Zhu, A. S. Tosun, Q. Deng. Sensor Placement for Lifetime Maximization in Monitoring Oil Pipelines.
11. A. Colorni, M. Dorigo, V. Maniezzo. Distributed optimization by ant colonies. Proceedings of ECAL'91. *European Conference on Artificial Life*. Elsevier Publishing. Amsterdam; 1991.
12. M. Dorigo, V. Maniezzo, A. Colorni. The ant system: an autocatalytic optimizing process. Politecnico di Milano;1991. *Technical Report TR91-016*.
13. M. Dorigo. Optimization, learning and natural algorithms. *Ph.D. Thesis*, Politecnico di Milano: Milano; 1992.
14. http://www.jandp-group.com/project.asp?pid=1009